ULSAN NATIONAL INSTITUTE OF SCIENCE AND TECHNOLOGY

Master's Thesis

EMERGING FIRMS IN AUTONOMOUS VEHICLE LANDSCAPE: AN EXPLORATORY ANALYSIS ON THEIR TECHNOLOGICAL POSITIONS USING GLOBAL PATENT DATA

Jiwon Lee

Graduate School of Technology and Innovation Management

UNIST

2021

EMERGING FIRMS IN AUTONOMOUS VEHICLE LANDSCAPE: AN EXPLORATORY ANALYSIS ON THEIR TECHNOLOGICAL POSITIONS USING GLOBAL PATENT DATA

Jiwon Lee

Graduate School of Technology and Innovation Management

UNIST

Emerging Firms in Autonomous Vehicle Landscape: An Exploratory Analysis on Their Technological Positions Using Global Patent Data

A thesis/dissertation
submitted to the Graduate School of Technology and Innovation Management, UNIST
in partial fulfillment of the
requirements for the degree of
Master of Technology and Innovation Management

Jiwon Lee

12. 23. 2020

Approved by

Advisor

Young-Choon Kim

ULSAN NATIONAL INSTITUTE OF SCIENCE AND TECHNOLOGY

Emerging Firms in Autonomous Vehicle Landscape: An Exploratory Analysis on Their Technological Positions Using Global Patent Data

Jiwon Lee

This certifies that the thesis/dissertation of Jiwon Lee is approved.

12. 23. 2020

Advisor: Young-Choon Kim

Yeolib Kim: Thesis Committee Member #1

Han-Gyun Woo: Thesis Committee Member #2

Abstract

This paper examines technology-based firms emerging in the field of autonomous vehicles and the mainline subclasses of their patent data. Drawing upon Cooperative Patent Classification (CPC) code, it considers the patent subclasses technological components of an invention. At a patent level analysis, it examines the trends of patent application, occupied subclasses and their combinations. At the firm level, it characterizes technology of the sampled firms by mapping their technology position and comparing inter-firm overlap. The findings demonstrate that the technological components and combinations of the inventions of these emerging firms focus primarily on data processing, transmission of digital information, and data recognition and presentation. The analysis on interfirm overlap shows that software or parts suppliers occupy relatively proximate positions as do vehicle sharing service providers. Autonomous vehicle manufacturers occupy relatively distant positions, implying that the technological categories of their inventions differ significantly. This study identifies the main technological components in the autonomous vehicle domain and evaluates innovations of the entrants and their competitive positions.

Table of Contents

List of Figures

List of Tables

1. Introduction

Innovation combines technological components in a novel manner and technological components mean any fundamental base of knowledge or matter that inventors use to build inventions. The inventions as combinations of these components and the accumulated outcomes of inventors refer to technological characteristics of innovators and the evolution of technological innovations can be conceived of as a landscape, with possible set of components corresponding to a particular position representing different configuration of components (Fleming and Sorenson, 2014). When an industry undergoes a transformation driven by technological innovations, new technologies and designs are introduced to the market and replace the old ones, known as creative destruction (Schumpeter, 1942). Followed by numerous inventions and entrepreneurial activities in the industry, the market accepts a new product architecture by the market. During this period of transformation, old incumbents and emerging firms interact and compete to control key technologies. When the incumbents introduce higher-quality products to satisfy the high end of the market, they overshoot the needs of low-end customers and many mainstream customers. This leaves an opening for entrants to find opportunities in the less-profitable segments that incumbents are neglecting. The entrants improve the performance of their offerings and move upmarket, challenging the dominance of the incumbents (Christensen et al., 2015).

The automotive industry is probably one of the best examples facing the transformation. It has traditionally been a paradigm of an oligopolistic sector and fierce competition has stimulated fast technology development and innovation. With the wave of digital transformation led by technology-based emerging firms, the era of autonomous vehicle has risen. These emerging firms are invading and pioneering the niche of new dominant design of shared, digital, and electric autonomous vehicles. Their inventions are the outcome of the firm strategy and trajectories along with intense research and development (R&D), and their technological characteristics and competitiveness can be represented by patenting in this technology-driven industry. In this regard, the technological characteristics of these emerging firms based on their patent data need to be examined by fine-grained measures to grasp the technology landscapes of this area of innovation. This paper utilizes the concept of existing methodologies for measuring technology landscape from the prior research done by Aharonson and Schilling (2016) and Stuart and Podolny (1996) in recombinant and local search. The results of this paper contribute to the application of these measures to examine the dynamics of technology components and their combinations, as well as competitive positions of the emerging firms based on their inventions.

This paper explores the technology landscape in autonomous vehicle industry, with special attention to the technology-based emerging firms and their patent data. The primary objective of this paper is to provide a comprehensive and up-to-date pictures of technology trends and emerging innovators in autonomous vehicle industry. First, it overviews the autonomous vehicle industry, including the change in industry dynamics and detailed explanation of autonomous vehicle technology and its evolution. Next, it reviews literatures regarding measuring technological capabilities and mapping technology landscape. Next is empirical analysis as following: investigation of basic profiles of 20 emerging firms in the autonomous vehicle domain, technology level analysis using their patent data, and firm level analysis by mapping their technological positions. Lastly, it concludes with discussion, limitation of the research, and direction for the further research.

2. Transformation of Automotive Industry

The global automotive industry is a pillar of the global economy, a main driver of macroeconomic growth and technological advancement for the major countries in the world, spanning many adjacent industries. In 2019, the U.S. automotive manufacturing industry contributed 2.4% to U.S. gross domestic product. That is 656 billion dollars out of the total 85.7 trillion dollars produced (U.S. Bureau of Economic Analysis, 2020).

Two major trends of decarbonization and digitalization has made the automotive industry face a challenge of establishing a new dominant design of a car, 'autonomous vehicle'. The automotive sector has traditionally been a 'fortress-industry' that original equipment manufacturers (OEMs) hold a stable position with little chance of being displaced by entrepreneurs (Ferras-Hernandez et al., 2017). However, the industry has faced a new wave of entrepreneurial dynamics and technological innovation, led by technology-based emerging firms like Tesla. The automotive industry, traditionally centered on finished car companies, has increased the role of information and communications technology (ICT) since the functional features of a car has changed from mechanical aspects to shared, digital, and electric aspects. This technological shift has naturally changed the structure of the automotive industry from vertical type centered on manufacturing and sales to a horizontal partnership between finished cars and part suppliers. It has lowered the entry barriers of the automotive industry, and the race is on with these entrants that have no track record in vehicle design, but a lead in software, sensors, Artificial Intelligence (AI), and communication technologies. Now, the time of stability is over and the entrants are creating new competition and cooperation dynamics targeting specific segments in automotive industry. They are penetrating this oligopolistic market as a new OEMSs, software or parts supplier, or vehicle sharing service providers (Ferras-Hernandez et al., 2017). The new OEMs like Tesla and Google are penetrating the oligopolistic market with aggressive technology developments and vehicle sharing service providers such as Uber and Zoox are creating new business models for automobile usage and ownership (Roland Berger, 2016). This new wave of entrepreneurial dynamics and industry diversification has heated up recently and the global autonomous vehicle industry is expected to be 7 billion dollars in 2020 and 656 billion dollars in 2030 (KPMG, 2020).

The existing automakers have been actively promoting R&Ds and collaborations or M&As with ICT companies with primary focus on maintaining their market share and gradual development of autonomous vehicle technologies based on their massive research and innovation capabilities and a long experience in vehicle-related technologies. For instance, Ford Motors has entered partnership with Velodyne, a leading company in Light Detection and Ranging (LiDAR) market, and with FLIR Systems and Veoneer specialized in thermal sensor and imaging camera in 2019. They announced that they are aiming to launch autonomous vehicle in Texas, Miami, and Washington DC in 2021. Volkswagen, who hold the top R&D budget in the automotive industry, said it would allocate nearly half its investment budget of 150 billion euros on e-mobility, hybrid cars, a seamless software-based vehicle operating system and autonomous driving technologies. Daimler has entered partnership with Bosch, BMW, and Audi in 2019 to launch platforms for autonomous driving pilotage until 2021 (KDB Future Research Institute, 2020).

Compared to the existing automakers, the entrants in autonomous vehicle industry have pursued relatively aggressive strategies to implement level 3 or higher levels at once based on AI and software technologies. Tesla, an American Electric Vehicle (EV) manufacturer, launched Autopilot in 2015, a built-in software for hands-free control for highway and freeway driving. Waymo, Google's subsidiary for autonomous vehicle project, has already offered 1,500 cases of robo-taxi service in Arizona with 20 million miles of mileage and 10 billion times of simulation test since 2016. It announced it will expand its commercial service in Los Angeles and Florida in 2021. Lastly, according to California Department of Motor Vehicle's Disengagement Reports in 2019, Zoox, a robo-taxi company founded in 2016, was evaluated as one of top 3 leading firms in autonomous vehicle testing, and was acquired by Amazon in 2020, aiming to release Amazon's first robo-taxi in 2021 (KDB Future Strategy Research Institute, 2020).

3. Emergence of Autonomous Vehicle

Autonomous vehicle refers to a vehicle capable of sensing its environment and moving safely with little or no human input. In 2016, Society of Automotive Engineers (SAE) announced 'J3016', a standard for self-driving vehicles, representing a degree of automation from 'Level 0' (no automation)' to 'Level 6' (full automation without driver's control) (SAE International, 2018).

Advanced Driver Assistance Systems (ADAS) currently equipped in most vehicles including adaptive cruise control, lane-keeping assistance systems, hill-start and park assist, and automatic braking systems in limited situations are 'Level 2' technologies.

--- Figure 1 here ---

European Patent Office (EPO) divides autonomous vehicle technologies into two main sectors. The first sector is 'automated vehicle platform' (technologies that are embodied in the vehicle itself) with three fields: 1) Perception, 2) Analysis and decision, and 3) Vehicle handling and underlying computing technologies. The second sector is 'smart environment' (technologies that enable automated vehicles to interact with each other and with their surroundings) with two fields: 1) 'Communication technologies', and 2) 'Smart logistics' (European Patent Office, 2018).

Autonomous vehicles are operated through three main processes: 1) 'Perception' (sensor and analysis), 2) 'Decision', and 3) 'Control'.

--- Figure 2 here ---

'Perception' consists of sensors (Radar, camera, night vision, etc.) to receive information and signals of the surrounding conditions of vehicle, and signal processing algorithms. Besides sensor technology, high-precision GPS technology, real-time local precision map construction, and database construction are also perception technologies for precise measurement of locational information.

'Decision' technology is related to Artificial Intelligence (AI) and software for vehicles, and it is a key technology for autonomous driving involved in all self-driving stages. Previously, rule-based software algorithms were used using expensive specialized sensors, but AI technology was applied to general sensors in image perception areas. In addition, artificial intelligence technology is also used to optimize routes, determine situations, predict collisions, and respond to unexpected situations. Currently, relevant software is divided into separate process of perception, decision, and control operated by function, but end-to-end method that implements the entire process through AI is also under research and development.

‘Control’ is a technology that appropriately controls vehicle's actuator, such as braking, steering, and acceleration mounted on the vehicle. Although self-driving of existing internal combustion engine-based vehicles is also possible, motor-based electronic actuators such as EVs are more advantageous for more precise control (KDB Future Strategy Research Institute, 2020).

The main technology other than driving is network technology. This includes various sensors and transportation infrastructure inside and outside the vehicle, as well as V2X (Vehicle to Everything) communication technology that enables vehicle-to-vehicle, vehicle-to-person and vehicle-infrastructure communication. The network technology increases driving safety by connecting to traffic infrastructure and control center and identifying traffic environment information (Connected Type) by utilizing cooperative communication technologies such as V2X, rather than relying solely on the vehicle's sensors. As the self-driving phase increases, urban infrastructures such as smart cities should be combined, such as standards for supporting communication between road infrastructure (signal lights, guardrails, street lights, bus stops, etc.) and systems for interworking and integrated information control between them.

Other technologies include the provision of passenger information, management of transfer of driving control, and Human Vehicle Interface (HVI) technologies for human-vehicle interaction, user information and convenience.

The automotive electronics appeared in the 1980s for engine control purposes, and now account for about 40% of the automobile manufacturing cost. In the 2000s and beyond, ADAS that can enhance safety specifications of vehicles and assist drivers have begun to appear in the auto industry, which has significantly boosted sensor and micro controller market. The sensor market including cameras and ultrasonic sensors for safe driving assistance, has grown rapidly to enhance the quality of autonomous driving technologies. More than 20 ADAS sensors are attached to one vehicle, including a camera, radar, LiDAR, night vision, and front and rear ultrasonic sensors (POSCO Research Institute, 2019).

According to EPO's report in 2018, from 2008 to 2017, 17,735 patent applications relating to SDV technologies were filed at the EPO. The number of annual applications remained stable just below 1,000 between 2008 and 2011, and it started to rise sharply in the years immediately following, reaching almost 4,000 in 2017. Before 2012, a large majority of patents fell into the 'Automated vehicle platform' sector. However, more recently, inventions relating to the 'Smart environment' sector have been growing faster and catching up in importance. Smart environment technologies now comprise a greater proportion of SDV patent applications, with the ratio between applications in the two sectors going from 0.4 in 2008 to 0.8 in 2015. In total, 8,627 applications have been filed in 'Smart environment', and 13,723 in 'Automated vehicle platform', whereby 4,615 (26% of the total) are associated with technologies in both sectors.

Between 2000 and 2015, total 24,311 inventions relating to autonomous vehicle technologies were subject to one or more patent applications in Europe. The annual number of these autonomous vehicle inventions grew six-and-a-half-fold between 2000 and 2015. Approximately one third of the inventions have been classified in established technology classes for automotive technologies ('Overlap'). The remaining two thirds represent technologies that go beyond the established technologies and are mainly related to information and communication technologies ('No overlap'). Both of them are growing at a similar pace. This suggests that the growth of autonomous vehicle technologies is largely driven by the integration of ICT with established automotive technologies (European Patent Office, 2018).

Recently, players with forward and backward linkage with automotive industry are actively jumping into the competition to dominate the infrastructure market for autonomous vehicle. This is because the autonomous vehicle infrastructure industry is a convergent industry that does not belong to a single industry group, has relatively low entry barriers, and plays a key role in taking the hegemony of the future autonomous vehicle industry. In the traditional automobile industry, the added value of parts industry remained low since parts suppliers had to go through many steps to supply their products to finished car manufacturers, but in the autonomous vehicle industry, the importance of the core infrastructure technologies has significantly increased. Now, companies from various industries, including ICT, electronic components, and car-sharing service, are focusing on developing autonomous driving software, computing platforms, and system operation to take a leading role and integrate the existing value chain in the autonomous vehicle industry.

4. Literature Review on Technological Capabilities and Technology Landscape

This paper is based on the perspective that an invention is a combination of technological components and it reviews literatures from the field of recombinant or local search to support this perspective. The technological components can be either familiar or unfamiliar to an inventor and one's domain knowledge, knowledge in distinct technological domains, and architectural knowledge, knowledge about how to combine elements from different technological domains affect new technology introduction and usefulness of the invention. The literatures reviewed in this paper utilize patent subclass or citation to introduce the notion of technological components and combinations in technology landscape, their relationship with technological innovation, inventor's search process to deepen and broaden their knowledge, and firms' technological capabilities for breakthrough invention.

Aharonson and Schilling (2015) have developed and applied a set of measures that enable fine-grained characterization of technological capabilities based on the USTPO database, dividing patents based on their mainline subclass information. The measures capture the distance between two patents and help to identify "outlier" patents - patents that pioneer uncharted territory in the technology landscape. They also provide a rich characterization of a firm's technological footprint, including its depth and breadth. The measures also assess the technological overlap, similarity, and proximity of the technological footprints of two or more firms. At the level of the macro technology landscape, the measures can be used to explore dynamics such as technology agglomeration, knowledge spillovers, and technology landscape evolution.

Fleming (2001) proposes that technological change is highly uncertain and unpredictable and explores the ultimate sources and causes of that uncertainty. He asserts that purely technological uncertainty drives from inventors' search processes with unfamiliar components and component combination. Experimentation with new components and new combinations leads to less useful inventions on average, but it also implies an increase in the variability that can result in both failure and breakthrough. He has constructed negative binomial count and dispersion models with patent citation data demonstrating that new combinations are more variable. However, the reuse of components has nonmonotonic and eventually positive effect on variability.

Conceptualizing invention as a combinational search process and assuming scientific research increases the rate of technological advance, Fleming and Sorenson (2004) argue that science alters inventors' search processes, by leading them more directly to useful combinations, eliminating fruitless paths of research, and motivating them to continue even in the face of negative feedback. They explore which science accelerates the rate of invention and prove inventors attempt to combine highly coupled components. Therefore, the value of scientific research to invention varies systematically across applications.

Stuart and Podolny (1996) propose a network-analytic approach for identifying the evolution of firms' technological positions, utilizing patent citation data. Their research is based on the assumption that 'local search' constrains the direction of corporate R&D is central in evolutionary perspectives on technological change and competition. The technological positions represent the graphical and quantitative assessments of the extent to which firm's search behavior is locally bounded. The firms are positioned and grouped according to the similarities in their innovative capabilities. The research explores 10 largest Japanese semiconductor producers from 1982 to 1992, analyzing their strategic partnering and the evolution of their technological positions.

Yayavaram and Ahuja (2008) utilize patent data from the worldwide semiconductor industry from 1984 to 1994 to study the effect of the structure of organizational knowledge bases, or the patterns of coupling between their elements of technical knowledge, on the usefulness of inventions and knowledge-base malleability. The authors argue that organizational variations in coupling patterns between knowledge elements can be reflected in a spectrum of knowledge-base structures—varying from fully decomposable (the knowledge base is composed of distinct clusters of knowledge elements coupled together with no significant ties between clusters) through nearly decomposable (knowledge clusters are discernable but are connected through crosscluster couplings) to non-decomposable (no knowledge clusters emerge, as the couplings are pervasively distributed)—and that organizations may differ in the way they use their knowledge because of variations in their knowledge-base structure, rather than because of differences in the knowledge elements themselves. Results show that a nearly decomposable knowledge base increases the usefulness of the inventions generated from it, as measured by patent citations, and also the knowledge base's malleability or capacity for change.

Yayavaram and Chen (2015) investigate the effect of changes in a firm's knowledge couplings on its innovation performance. They explain how changes in couplings among existing knowledge domains and those between new and existing knowledge domains affect the generation of valuable inventions. The authors also examine how observed domain complexity, an indicator of the inherent interdependencies among knowledge domains, moderates the effects of changes in a firm's knowledge couplings on innovation performance. The results suggest that a change in couplings among existing knowledge domains hurts innovation outcomes, but not when the degree of domain complexity is high, whereas coupling new and existing knowledge domains leads to improved outcomes, but not when the degree of domain complexity is high.

Yayavaram, et al. (2018) explore technological alliances, emphasizing that search for knowledge drives alliance formation. However, in conceptualizing technological knowledge, prior work on alliances has not made a distinction between domain knowledge—knowledge that firms possess in distinct technological domains—and architectural knowledge—knowledge that firms possess about how to combine elements from different technological domains. The authors argue that firms seek partners that are similar in domain knowledge to deepen their knowledge, and partners that are dissimilar in architectural knowledge to broaden their knowledge. The results indicate that the likelihood of alliance formation increases when two firms are similar in domain knowledge and dissimilar in architectural knowledge. Further, the results show that these effects are positively moderated by the degree of decomposability of a firm's knowledge base.

In dynamic environments, companies need to continually deepen and broaden their technological knowledge, and they often look for alliance partners who can provide them that knowledge. For knowledge deepening, companies are more likely to form alliances with those companies that have expertise in similar technological fields. For knowledge broadening, they are more likely to form alliances with those companies that have expertise in the same technological fields but have different recipes for combining knowledge from those fields. Furthermore, a company with a modular knowledge base is more likely to seek a partner that has expertise in similar technological fields or whose recipes for combining knowledge from different technological fields are different from the recipes it has.

Katila and Ahuja (2002) examine how firms search, or solve problems, to create new products. According to organizational learning research, firms position themselves in a unidimensional search space that spans a spectrum from local to distant search. The findings in the global robotics industry suggest that firms' search efforts actually vary across two distinct dimensions: search depth, or how frequently the firm reuses its existing knowledge, and search scope, or how widely the firm explores new knowledge.

Jung (2015) examine firm exploration leading to breakthrough inventions with focus on a new dimension of knowledge search: the search of originality. The author conceptualized firm search types with two distinct dimensions, search target and search boundary, and proposes contrasting effects of the search boundary in which firms search prior original knowledge on the propensities for firms to create path-breaking novelties and high-impact breakthroughs. In particular, the author demonstrates that searching original knowledge and incorporating it into research and development makes local search outperform boundary-spanning search in generating high-impact breakthroughs. Jung argues that this advantage of local search arises from the originality that firms search and revitalize. This research undertakes the analysis of American firms' nanotechnology patents between 1980 and 2006. The findings highlight the importance of searching original knowledge and the benefit of local search in creating breakthrough inventions, thereby suggesting a refinement of the conventional framework of knowledge search.

5. Empirical Analysis

Technological capabilities represent what the firm can do in the present, as well as what it has learned in the past. These capabilities also have a significant influence on the trajectories a firm will choose in the future (Aharonson and Schilling, 2015). A firm with high technology capabilities makes many breakthrough inventions and recombination of the knowledge elements are required for these inventions. (Fleming and Sorenson 2004, Kauffman 2000). Based on which knowledge elements firms have based their invention, interfirm comparison on technological overlap or similarity can be done.

This paper characterizes the technological characteristics of emerging companies in autonomous vehicle domain utilizing their patent classification information. At a patent level analysis, it explores the trends of these firms' issued patents in terms of occupied subclasses as knowledge elements and combinations of these subclasses, which refers to technology positions. At the firm level analysis, it explores technological characteristics of these firms by mapping their interfirm position and comparing their proximity based on the technological categories of their patents.

5.1. Sample

The research sample for the empirical analysis is patent subclasses of technology-based emerging companies in autonomous vehicle domain, founded after 2000. It uses Crunchbase database to search these firms and identify their profiles.

Crunchbase is an international commercial database which contains business information about innovative start-ups and emerging companies. Crunchbase, Inc. was founded in 2007 to track the startups that its parent company TechCrunch featured in articles. Crunchbase database provides information on companies and their individuals such as company size, location, status, founding date, equity investment, and founders' career and educational background. The database is becoming increasingly popular with scholars and researchers, particularly as a source of information on start-up activity and financing within and across countries. (Dalle et al., 2017)

The list of emerging companies in autonomous vehicle domain was collected using following filters on Crunchbase Pro's query builder:

--- Table 1 here ---

Since autonomous vehicle supplier or third-party suppliers began to appear in the automobile market in 2000s, the research target was set as private companies that have started their business since 2000. Additionally, equity investment is one of the key factors for assessing potential and value of an emerging company. In this regard, firms with total equity funding amount greater than or equal to $10,000,000 were searched on Crunchbase.

The data was extracted on July 15th, 2020 and the initial sample consisted of total 154 companies. These firms then were listed in descending order of total equity funding amount and top 20 companies among them were finally selected as the target for the patent data. The proportion of total equity funding amount of these 20 firms takes up approximately 81% of that of the entire 154 companies. Since these companies can be regarded as leaders representing emerging companies in the autonomous vehicle domain, this paper compares their interfirm technological positions based on their patent data. Below is the list of the 20 companies and their basic profile.

--- Table 2 here ---

Crunchbase organizes industries of the listed companies into 47 'Industry Groups' such as 'Artificial Intelligence', 'Commerce and Shopping', 'Consumer Electronics', 'Energy', 'Transportation' and so on (Crunchbase, 2020). Under these groups, more than 700 industries are organized as 'Industries' on the database. For example, industries such as 'Cloud Data Services', 'Cloud Security', and 'Data Visualization' belong to the industry group called 'Information Technology'. 'Autonomous Vehicles' industry belongs to industry group of 'Transportation'.

The top 20 companies that belong to the autonomous vehicles industry in the Crunchbase database also report additional industry domains of their operation. The distribution of these additional industry domains includes Automotive (75%), Transportation (60%), Robotics (25%), Electric vehicle (25%), Software (15%), Artificial intelligence (15%), Manufacturing (15%), Electronics (10%), Mobile (10%), Innovation management (5%), Sensor (5%), Industrial automation (5%), Information technology (5%), GPS (5%), and Fleet management (5%) (See Figure 3).

--- Figure 3 here ---

Figure 4 represents the number of companies by country of origin. Out of the 20 companies, 12 firms (60%) are based in United States – and among them, 9 companies (45%) are headquartered in California. Besides them, the rest of the companies are headquartered in China (30%) and Israel (10%).

--- Figure 4 here ---

10 firms (50%) have received investment between 250 million dollars and 1 billion dollars. 5 firms (30%) have obtained total equity funding between 1 billion and 3 billion dollars, and the rest of 4 companies (20%) have received investment more than 3 billion dollars.

5.2. Patent Data

For these 20 emerging firms in autonomous vehicle domain, this paper collects their patent data using Google Patent database.

There are three main ways of protecting intellectual property: patent, copyright, and trademark. A patent protects an invention, and a trademark protects words or symbols intended to distinguish the source of a good. A copyright protects an original artistic or literary work. In many countries, inventors can apply for patent protection for their inventions. In the United States, a patent is a property right granted by the federal government that excludes others from producing, using, or selling the invention in the United States, or from importing the invention into United States, for a limited time in exchange for public disclosure of the nature of the invention at the time the patent is granted.

The first step in securing a patent is to file a patent application. The application generally contains the title of the invention, as well as an indication of its technical field. It must include the background and a description of the invention, in clear language and enough detail that an individual with an average understanding of the field could use or reproduce the invention. Such descriptions are usually accompanied by visual materials – drawings, plans or diagrams, - that describe the invention in greater detail. The application also contains various 'claims', information to help determine the extent of protection to be granted by the patent. An invention must fulfill the following conditions to be protected by a patent. It must be of practical use; it must show an element of 'novelty', meaning some new characteristics not part of the body of existing knowledge in its particular technical field. That body of existing knowledge is called ‘prior art’. Patents are granted by national patent offices or by regional offices that carry out examination work for a group of countries, for example, the European Patent Office (EPO) (World Intellectual Property Organization, 2004).

A patent owner has the right to decide who may or may not use the patented invention for the period during which it is protected. Patent owners may give permission to, or license, other parties to use their inventions on mutually agreed terms. Owners may also sell their invention rights to someone else, who then becomes the new owner of the patent. Once a patent expires, the protection ends and the invention enters the public domain. This means the owner no longer holds exclusive rights to the invention, and it becomes available for commercial exploitation by others. A patent granted in one country does not provide protection in the other countries. Firms seeking patent protection in multiple countries must apply in each of the countries in accordance with those countries’ requirements (Schilling, 2008).

Automotive and digital technologies are both very innovative sectors and this makes autonomous vehicle industry a crossover of these two sectors. Many of the underlying technologies of autonomous vehicles have been already invented by numerous companies to commercialize fully autonomous vehicle in near future and thousands of patent applications have been filed to secure the IP rights to the companies. These patent applications define the technologies used in autonomous vehicles and can offer unique insights into the direction a technology is heading, and which companies and countries are in the lead.

This paper utilizes patents filed by aforementioned 20 firms from 2000 to 2019 to measure and characterize technological position of their inventions and their interfirm overlap based on their patents. Every patent that these companies are registered as assignees was collected from Google Patent database. In total, 3,845 patents were collected.

5.3. Technological Component and Position

Technological inventions can be an outcome of a recombination of existing knowledge elements (Fleming, 2001). The notion of technological inventions can be conceived as a landscape, with each potential position on the landscape corresponding to a particular configuration of components (Fleming and Sorenson, 2004). These components can be regarded as a knowledge base of an invention, and particular set of these combinations represents a technology position of an invention or inventor. Some positions may be occupied by existing innovations, while others can be conceived as unique positions.

Aharonson and Schilling (2016) have measured distance between technology positions of patents in the United States Patent and Trademark Office (USPTO) database. First, they create a binary technology vector for each technology position based on the patents' mainline subclasses. Each subclass is conceived as an individual component of a technology vector and the occupied subclass is represented as '1' and '0' if not. Next, they have calculated technological distance between these positions. Technology positions were defined as 'adjacent' positions if only one component of their vector differs. For example, the vectors 00011100 and 00001100 are adjacent as they differ only in the value taken by the fourth component. Then, path length between every pair of occupied technology position was calculated based on these adjacencies. If multiple years of data being compared, this path length measure should be computed for each year to reflect the change of technological landscape.

In this paper, to measure and characterize technological position and characteristics of 20 technology-based emerging firms in autonomous vehicle domain, every patent that these companies are registered as assignee was collected using Google Patent database. To measure technological characteristics of these firms in finer granularity and detail, mainline subclasses of each patent based on Cooperative Patent Classification (CPC) was utilized as a technological component of a technological position. Using mainline subclass of a patent provides better clarity about functionality of an invention compared to using a main class. (Benner and Waldfogel, 2008).

The Cooperative Patent Classification (CPC) is a patent classification system developed by the United States Trademarks and Patent Office (USTPO) and the European Patent Office (EPO). The CPC scheme is based on International Patent Classification (IPC) system, consisting of hierarchical structures with symbols of Section, Subsection, Class, Subclass, Main group, and Subgroup (See Figure 5). Each patent can be assigned to one or more classes and/or subclasses.

--- Figure 5 here ---

This paper conceives a mainline subclass of a patent as a technological component of an invention. Therefore, most frequently occupied subclasses and combinations of subclasses will be investigated, to figure out the main components and analyze the dynamics of the components in terms of technology landscape.

5.4. Cross-firm Overlap in Technological Characteristics

Stuart and Podolny (1996) characterizes inventive activities of firms as 'local search', implying that firms' inventions share technological content with the outcomes of their prior searches. They propose a network-analytic methodology to measure the technological landscape produced by the simultaneous search activities of a group of high-technology firms. A firm's position in this landscape derives from the overlap of its inventive activities with those of its competitors.

In their research, a relational construction of technological positions is proposed, such that firms that have developed portfolios consisting of similar technologies are located near to one another. Firms' abilities to develop technologically similar inventions reveal proximities in their underlying knowledge base, and firms' technological positions reflect the characteristics of their innovative activities.

Utilizing firms' patent citations, Stuart and Podolny (1996) assess the degree of interfirm path dependencies of 10 largest Japanese semiconductor producers from 1982 to 1992. The authors define the technological overlap between the members of a pair of firms if they build on the same foundations for their current inventions. They express complete information about interfirm technological overlaps for N innovators in an asymmetric matrix of order $N \times N$, known as 'community matrix'. The elements of this matrix are called 'competition coefficients', and notation α_{ij} was used to denote the proportion of firm i's niche that is occupied by another firm j. Notation α_{ji} is the proportion of firm j's niche that is occupied by firm i. The value of α_{ij} and α_{ji} ranges between 0 and 1. The value of 0 implies the two firms are completely differentiated and value of 1 implies j fully occupies firm i's niche and vice versa. The technological overlap implies that the two firms are sharing knowledge base of their inventions. The competition coefficients are defined as:

$$\alpha_{ijt_m} = \frac{\sum_{v=1}^{p} \alpha_{ivt_m} \alpha_{jvt_m}}{\sum_{v=1}^{p} \alpha_{ivt_m}}$$

$$\alpha_{jit_m} = \frac{\sum_{v=1}^{p} \alpha_{ivt_m} \alpha_{jvt_m}}{\sum_{v=1}^{p} \alpha_{jvt_m}}$$

where v denotes a technological antecedent, and p indexes the total number of distinct antecedents that were foundations for the sampled firms at time t_m. The ijth cell in the matrix is the total number of the common antecedents of i and j's invention at time t_m divided by the number of i's invention occupied by its technological antecedent. Except for cases when the antecedents of i and j do not overlap (value of both cells will be zero), the denominator in the equation will almost differ and the ijth and jith cells will not be equal to one another.

Next, using the competition coefficients, they calculate Euclidean distance between firm i and j at time t_m which represents the degree to which firm i and j have a similar pattern of niche overlap with all the other firms k. Based on this measure, the distance between different firms in different time periods was represented in a symmetric matrix, where cell it_lt_m represents the difference in the pattern of overlap between firm i at time t_l and firm j at time t_m. The elements of this distance matrix are defined as:

$$d_{it_ljt_m} = d_{jt_mit_l} = \left(\frac{n-2}{n-1}\right)^{\delta} \left\{ \sum_{k=1}^{n} \left[\left(a_{ikt_l} - a_{jkt_m}\right)^2 + \left(a_{kit_l} - a_{kjt_m}\right)^2 \right] \right\}^{1/2}, k \neq i, j$$

Notation δ equals 1 if $i = j$ and $l \neq m$, and 0 otherwise. The dimensions of this symmetric matrix are $N \times T$ rows by $N \times T$ columns, where N is the number of firms and T is the number of time periods.

Finally, the information in the symmetric distance matrix was converted to a graphical representation of interfirm distances using multidimensional scaling (MDS) routines. MDS is a means of visualizing the level of similarity of individual cases of a dataset. It is used to translate information about the pairwise distances among a set of n objects into a configuration of n points mapped into an abstract Cartesian space (Mead, 1992).

Where Stuart and Podolny (1992) use patent citations made by sample of 10 semiconductor firms, this paper utilizes patent subclasses of 20 emerging firms to explore their niche overlap and technological positions in the autonomous vehicle industry. Where defining niche overlap using patent citations identifies the extent to which the sampled firms build on the same foundations for their current invention, the measures in this paper using patent subclass information define the sampled firms' niche overlap based on specific technological categories of their current inventions. It defines how much of the subclasses of patent of the paired firms overlap, and how distant the firms are based on the technological features of their inventions.

5.5. Exploratory Analysis

The exploratory analysis utilizing patent data is comprised of two levels, firstly a patent level basis to identify the trends of patents and technology components and their combinations, then a firm level basis to measure and compare the interfirm overlap based on their technological positions.

5.5.1. Descriptive Analysis on Technology Components and Positions

The patent-level analysis explores technological landscape of autonomous vehicles domain utilizing top 20 companies' patent data from 2000 to 2019. First, it identifies the number of patent application. Next, the number of occupied subclasses of these patents and their frequencies were counted and visually represented. Lastly, the combination of these subclasses, which is a technology position of a patent, was identified.

Figure 6 shows the number of patent applications from the 20 firms from 2000 to 2019. Total 3,845 patents are filed and the number of patent applications shows increasing trends in overall. Until 2008, the patent applications fluctuate in small range between 15 and 49. In 2009, the number of filed patents doubles from the prior year and the range of fluctuation also increase between 77 and 148. In 2015, the number of patent applications begins to increase drastically and 1,029 patents are filed in 2017.

According to the U.S. Code § 122, patent application is disclosed to the public after 18 months from the earliest filing date. Since the patent data from Google Patent was collected in July 2020, most of the patent applications filed after the beginning of 2019 are not included in the dataset. Therefore, only 155 patents were collected for 2019 from Google Patent and the analytic results afterwards might not fully reflect the patents filed after 2019.

---Figure 6 here ---

These 3,845 patents occupy 205 subclasses in total. Table 3 shows the description and frequency of 10 most occupied subclasses overtime. Subclass related to control systems for sub-units of hybrid road vehicles (subclass B60W) is the most occupied subclass of all, 2,194 times in total. Next most frequently occupied subclass is G06Q, related to data processing systems. It is followed by subclass G05D, systems for controlling or regulating non-electric vehicles. Next is subclass G01S, related to technologies using radio waves, such as direction finding, navigation, determining distance or velocity, locating or presence-detecting. Rest of the subclasses are related to electric digital data processing, recognition and presentation of data, image data processing or generation, measuring distance/gyroscopic instruments/photogrammetry or videogrammetry, traffic control systems, and transmission of digital information.

--- Table 3 here ---

The trends of these 10 most occupied subclasses based on their frequency is graphically represented in Figure 7. The frequency of the subclasses shows small or no increase between 2000 and 2008. It begins to slightly increase after 2009 and shows higher increasing rate in 2012. The three most frequent subclasses, B60W, G05D, and G06Q, soar in 2017, from 209, 186, and 346 to 716, 708, and 710. Rest of the subclasses also peak in 2017, with frequency ranging between 229 and 428.

--- Figure 7 here ---

Next, combinations of the subclasses of the patents are explored. As mentioned earlier, the combination of technological components, which is a set of subclass(es) a particular patent occupies, refers to a technological position of a certain technology. Table 4 shows 10 most frequent technological positions overtime and their trends are graphically represented in Figure 8.

8 out of 10 positions are combinations comprised of single subclass. Among these 8 positions, 7 positions overlap with the most frequently occupied subclasses shown in Table 3

and Figure 7. Out of these 8 positions, 4 positions are related to processing and transmission of digital data. Throughout the operational process of autonomous vehicle, enormous amount of data is generated, transmitted, and processed. Therefore, the overall quality of the 'autonomous' operation of the system is mainly related to data processing and this accounts for majority of the results of this analysis comprised of the processing and transmission of digital data. Subclass H01M is the only newly appeared subclass among these 8 positions comprised of single subclass. This subclass is relevant with processes or means regarding batteries. One of the main technological issues in the autonomous vehicle industry is enhancing the quality of built-in batteries. To increase the reliability and price competency of autonomous vehicle, enhancing the efficiency and duration of batteries is essential in the industry. Elon Musk, the Chief Executive Officer (CEO) of Tesla, announced in September 2020 that Tesla aims to produce batteries at 56% of the current cost in 2023. In this regard, an intense R&D on the batteries would have been proceeded in the industry and the results could have been reflected on the outcome of this paper's analysis on technological positions. The rest of 2 positions are combinations of two subclasses: 1) G06Q and H04L and 2) G06F and G06Q. All of these subclasses are recombinations of the aforementioned subclasses relevant to processing and transmission of digital data.

--- Table 4 here ---

These 10 technological positions appear 973 times in total. Positions related to data processing, transmission of digital information, and recognition and presentation of data take approximately 75% of the total frequency of 10 positions (741 times). These positions include combinations comprised of single subclass of G06Q, G06F, H04L, and G06K and two subclasses of G06Q and H04L, and G06Q and G06F. Patents related to cellular network or signal security, multi-tasking, parallel processing, and system prioritization fall into these positions.

The remaining 25% of the positions are comprised of single subclass of G01C (78 times), G08G (61 times), G01S (51 times), and H01M (42 times). Subclass G01C includes patents related to sensor fusion, data fusion, and localization and navigation. Patents related to high definition maps, wireless communication, vehicle connectivity, automated parking fall into subclass G08G. Sensor-related patents such as LiDAR and radar are included in subclass G01S. Subclass H01M includes patents related to batteries and hybrid vehicles.

The first and second most occupied positions, G06Q and G06F appeared 387 and 161 times each. The frequency of these two positions takes about 56% of the total frequency of the 10 positions. These two show the highest increasing rate in 2015, and G06Q peaks in 2018 with 126 frequencies and G06F in 2017 with 47 frequencies. 82% and 77% of the total frequency of G06Q and G06F appeared between 2016 and 2018.

Except for the position H01M, frequency of the all positions is also concentrated between 2016 and 2018, with occupancy rate of higher than 50% (G01C: 65%, G08G: 67%, H04L: 55%, G01S: 59%, G06K: 72%, G06Q+H04L: 51%, H01M: 19%, G06F+G06Q: 80%).

--- Figure 8 here ---

5.5.2. Descriptive Analysis on Interfirm Overlap in Technological Characteristics

First, a 20 x 20 community matrix of the 20 sampled firms is constructed (See Table 5). The matrix is created using subclasses of these 20 firms' patents applied from 2000 to 2019. Each value of the competition coefficient represents the degree of overlap between two firms. For instance, the value of $\alpha_{cruise\ tesla}$ is number of common occupied subclasses of Cruise and Tesla's patents, divided by the total number of occupied subclasses of Cruise's patents. It denotes the proportion of subclasses of Cruise's patents that is occupied by Tesla's. The numerator of $\alpha_{tesla\ cruise}$ is the same, the only difference is the denominator, which is the total number of occupied subclasses of Tesla's patents. It denotes the proportion of subclasses of Tesla's patents occupied by Cruise's. The value of the competition coefficients ranges from 1 to 0 and each row and column show the degree of overlap of two firms' niche based on their patents' mainline subclass information. For example, the first row represents how much all the other firms are in Cruise's niche and the first column represents the degree to which Cruise is present in the niches of all other firms. Zoox shows the highest degree of overlap in Cruise's niche, and Cruise occupies Aurora's niche the most.

--- Table 5 here ---

Next, using the competition coefficients, a 20 x 20 distance matrix spanning from 2000 to 2019 is constructed (See Table 6) and the values on this matrix are converted to a graphical representation of interfirm distances using the MDS (See Figure 9).

--- Table 6 here ---

--- Figure 9 here ---

The analyses in the MDS can account for partitioning the firms into strategic groups. If the firms' positions cohere in the configuration, it can be speculated that the technological components of their inventions are similar and they might perform analogous innovative roles and can be grouped into a same strategic group in the industry. That is, they compete with the other firms in the same group and can substitute for one another in their innovative roles.

Aurora Innovation and Innoviz Technologies cohere in the MDS configuration. Their core technologies are significantly similar, solid-state LiDAR sensor and perception software for autonomous vehicles, and this can account for their proximity in the MDS configuration.

The ride sharing service providers are all located on the upper left side of the MDS map: they are Uber, Waymo, Zoox, and DiDi. Uber neighbors with Waymo, Alphabet's (Google's parent company) subsidiary for autonomous vehicle. Waymo and Zoox also cluster and their businesses are catered to robo taxi service. DiDi occupies relatively isolated position apart from the ride sharing service providers. Even though Uber and DiDi provide similar business of car sharing service, their distance from each other is farther than their distance from other ride sharing service providers. Interestingly, Xiaopeng Motors is the only EV manufacturer positioned closer to those firms on the upper left side of the MDS map.

The technological positions of other autonomous vehicle manufacturers are relatively spread on the MDS configuration: they are Tesla, Fisker, WM Motors, LeSee, and Skio Matrix. Their distances from one another are farther than the distances between other non-manufacturers in the MDS. It can be interpreted that their technological niche does not overlap and their main technologies may differ. It is interesting that Fisker, one of the American autonomous vehicle manufacturers cohere with ClearMotion, a Massachusetts Institute of Technology (MIT)-born autonomous vehicle technology company that specializes in relatively narrow technological sector of proactive ride system.

6. Discussion and Conclusion

This paper explores the technological characteristics of emerging innovators in the autonomous vehicle industry and utilizes novel measures for mapping technology landscape based on their patent data. At the patent level, this paper shows the patenting trends of the autonomous vehicle industry, trends of major patent subclasses as technology components, and combinations of those components which are technological positions. At the firm level, it assesses cross-firm overlap based on the technological components of their patents. The proximity of interfirm positions depends on the degree to which they are pioneering similar technological niche. That is, two firms that occupy proximate positions in the technological space are assumed to perform similar roles as innovators and clusters of firms can be conceived of as grouping based on similar innovative activities (Stuart and Podolny, 1996).

By using the mainline subclasses rather than using patent class, this paper provides much more precise measures of technological positions. The dynamics of technological components as well as the positions of emerging leaders in the technological space can represent the key technologies and the competition dynamics in the industry and help firms or their managers decide in which technologies to invest in development, with whom to partner, assess their competitive positions, and formulate their R&D strategies and potential technological trajectories.

By exploring main technology components and combinations of emerging firms' patent in autonomous vehicle industry, the core technologies and past R&D trajectories of these firms can be identified. Most of their patents are related to data processing, sensors, navigation, wireless communication, and connectivity. It accounts for the necessity of R&D and crossover of various technological fields in ICT to develop an infrastructure of shared, digital, electric, and autonomous vehicle and lead the technological hegemony in this industry. Based on these results, existing automakers and firms in other relevant industries who are jumping into the competition can have insights about which technological components or combinations they should focus on or with whom they should partner to complement or diversify their technological niche. Emerging firms can also construct their R&D trajectories based on the understandings of the technological similarities of the emerging innovators.

Technological overlap on the innovative space based on their core technologies provides insights about their technological features in technology landscape. The leaders in the fields of sensor-based technologies like LiDAR and radar cohere on this space, implying that their technological characteristics are relatively similar in the autonomous vehicle industry. Also, the ride sharing service providers also have similar level of technological characteristics as innovators. However, the manufacturers of finished autonomous vehicle occupy relatively independent positions and it implies that their inventions have diversified technological features and the dominant design of autonomous vehicle is yet to be established and needs intense R&D and competition to raise the standards.

It must be noted, however, that these measures also impose some limitations. First, since the measures are based on patent data, this analysis is only useful for assessing firms for whom patents are a reliable indicator of their innovative activities. Second, this paper utilizes mainline subclasses of patents to explore technology landscapes, but arguably, one could create even finer-grained measures by using the lower level groups or subgroups of the patents. Third, this paper does not empirically compare the measures to the citation-based measures. The citation process of patents provides information on the lineage of the patent from the perspective of 'local search'. Though classification system of patents is designed to represent taxonomy and increase the efficiency of search, emphasizing the technological components and composition of the innovation, it is difficult to elaborate when it is better to use one over the other. Lastly, the analytic results are based on patent data of only 20 leading emerging firms in the autonomous vehicle industry. The range of sampled firms need to be expanded to provide the empirical analysis from broader and deeper perspective.

6.1. Directions for Further Research

The objective of this paper is to measure and represent the technology landscape of autonomous vehicle based on patent data. The empirical analysis in this paper is focused on the patent data of only 20 emerging firms in the autonomous vehicle industry, so the sample data should be expanded to larger scale to fully investigate the characteristics of the rest of the emerging companies. For instance, the patent level and firm level analysis can be done on 50 emerging firms in the autonomous vehicle industry. Moreover, it is be possible to make inter-sample comparisons in the same industry. For instance, one can compare patent data of 20 emerging firms to that of 20 incumbent automobile makers. The incumbents also pay important roles in terms of technological innovation, so the interaction and collaboration between the incumbents and the entrants should be studied and will provide insights pertinent to exploring the technology landscape of the autonomous vehicle industry from broader perspective.

References

Aharonson, B. S. and M. A. Schilling (2016). 'Mapping the technological landscape: Measuring technology distance, technological footprints, and technology evolution', *Research Policy*, **45**, pp. 81-96.

Benner, M., Waldfogel, J. (2008). 'Close to you? Bias and precision in patent-based measures of technological proximity', *Research Policy*, **37**, pp. 1556–1567.

Christensen, C. M., M. E. Raynor and R. McDonald (2015). 'What is disruptive innovation?', *Harvard Business Review*, **93**, pp. 44-53.

Crunchbase Product Team (2020). 'How are industries organized?', *Crunchbase*, support.crunchbase.com/hc/en-us/articles/360043671353-How-are-industries-organized-.

Dalle, J. M., M. D. Besten and C. Menon (2017). 'Using Crunchbase for economic and managerial research', *OECD Science, Technology and Industry Working Papers* 2017/08, OECD Publishing.

European Patent Office (2018). *Patents and self-driving vehicles: The inventions behind automated driving.*

Ferras-Hernandez, X., E. Tarrats-Pons and N. Arimany-Serrat (2017). 'Disruption in automotive industry: A cambrian moment', *Business Horizons*, **60**, pp. 855-863.

Fleming, L. (2001). 'Recombinant uncertainty in technological search', *Management Science*, **47**(1), pp. 117-132.

Fleming, L. and O. Sorenson (2004). 'Science as a map in technological search', *Strategic Management Journal*, **25**, pp. 909-928.

Fleming, L. and O. Sorenson (2008). 'Navigating the technology landscape of innovation', *MIT Sloan Management Review*, **44**(2), pp. 15-23.

Katila, R. and G. Ahuja (2002). 'Something old, something new: A longitudinal study of search behavior and new product introduction', *Academy of Management Journal*, **45**(6), pp. 1183-1194.

KDB Future Strategy Research Institute, (2020). *自律주행차 국내외 개발현황 [Status quo of domestic and overseas R&D on autonomous vehicles]*.

KPMG, (2020). *New changes in autonomous driving*.

Mead, A. (1992). 'Review of the development of multidimensional scaling methods', *Journal of the Royal Statistical Society*, **41**, pp. 27-39.

Nelson, R. and S. Winter (1982). *An evolutionary theory of economic change.* Cambridge.

Roland Berger (2016). *Global automotive supplier study*.

SAE International (2018). 'Levels of Driving Automation, URL', *SAE International*, https://www.sae.org/news/press-room/2018/12/sae-international-releases-updated-visual-chart-for-its-%E2%80%9Clevels-of-driving-automation%E2%80%9D-standard-for-self-driving-vehicles

Schilling, M. A. (2008). *Strategic management of technological innovation*. McGraw-Hill.

Schumpeter, J. (1942). *Capitalism, socialism, and democracy.* Harper & Brothers.

Podolny, J. M. and T. E. Stuart (1996). 'Local search and the evolution of technological capabilities', *Strategic Management Journal*, **17**, pp. 21-38.

POSCO Research Institute (2019). *스마트카 시대 자동차 新밸류체인: 커넥티드카, 자율주행차용 센서와 AI컴퓨터 트렌드 [New value chain in the era of smart cars: trends of connected car, sensors for autonomous vehicles, and AI computers].*

World Intellectual Property Organization (2004). *What is intellectual property?*

U.S. Bureau of Economic Analysis, Industry Economic Account Data: GDP by industry, URL: https://apps.bea.gov/iTable/iTable.cfm?reqid=150&step=2&isuri=1&categories=gdpxind (accessed: September 23, 2020)

Yayavaram, S. and G. Ahuja (2008). 'Decomposability in knowledge structures and its impact on the usefulness of inventions and knowledge-base malleability', *Administrative Science Quarterly*, **53**(2), pp. 333-362.

Yayavaram, S. and W. Chen (2015). 'Changed in firm knowledge couplings and firm innovation performance: The moderating role of technological complexity', *Strategic Management Journal*, **36**(3), pp. 377-396.

Yayavaram, S., M. K. Srivastava and M. Sarkar (2018). 'Role of search for domain knowledge and architectural knowledge in alliance partner selection', Strategic Management Journal, 39, pp. 2277-2302.

Appendix

This section of the paper utilizes European Patent Office (EPO)'s patent classification standards for autonomous vehicle-related patents. EPO categorizes CPC subclasses of these patents into two main categories of 'Smart environment' and 'Automated vehicle platform', then into five sub categories of 'Communication', 'Smart logistics', 'Perception, analysis & decision', 'Computing', and 'Vehicle handling'. Based on this taxonomy, this section of the paper constructs a five-digit binary vector representing the combinations of occupied subclasses. Each digit refers to forementioned EPO's five subcategories and 1 means occupied subclasses fall into these subcategories. For example, vector 10010 means the occupied subclasses are combination of 'Communication' and 'Computing' subcategories.

Figure 10 shows the trends of all technological positions of 3,773 patents of the 20 firms. Out of total 3,773 patents, 2,576 cases fall into vector 00000 meaning none of the subclasses fall into EPO's subcategories. Except for these cases, vector 00100 appears most frequently ('Perception, analysis & decision', 628 patents) out of the remaining 1,197 patents. Next is followed by vector 01000 ('Smart logistics', 112 patents), 10100 ('Communication' and 'Perception, analysis & decision', 89 patents), 01100 ('Smart logistics' and 'Perception, analysis & decision', 79 patents), 10000 ('Communication', 68 patents), 00110 ('Perception, analysis & decision' and 'Computing', 63 patents), and 11100 ('Communication', 'Smart logistics', and 'Perception, analysis & decision', 34 patents).

Among these technological positions, a position that appeared only once as a patent between 2000 and 2019 can be regarded as a unique combination of technological element(s). These are vector 01011 ('Smart logistics', 'Computing', and 'Vehicle handling', Tesla, 2008), 10010 ('Communication' and 'Computing', Byton, 2018), 10101 ('Communication', 'Perception, analysis & decision', and 'Vehicle handling'), and 11110('Communication', 'Smart logistics', 'Perception, analysis & decision', and 'Computing').

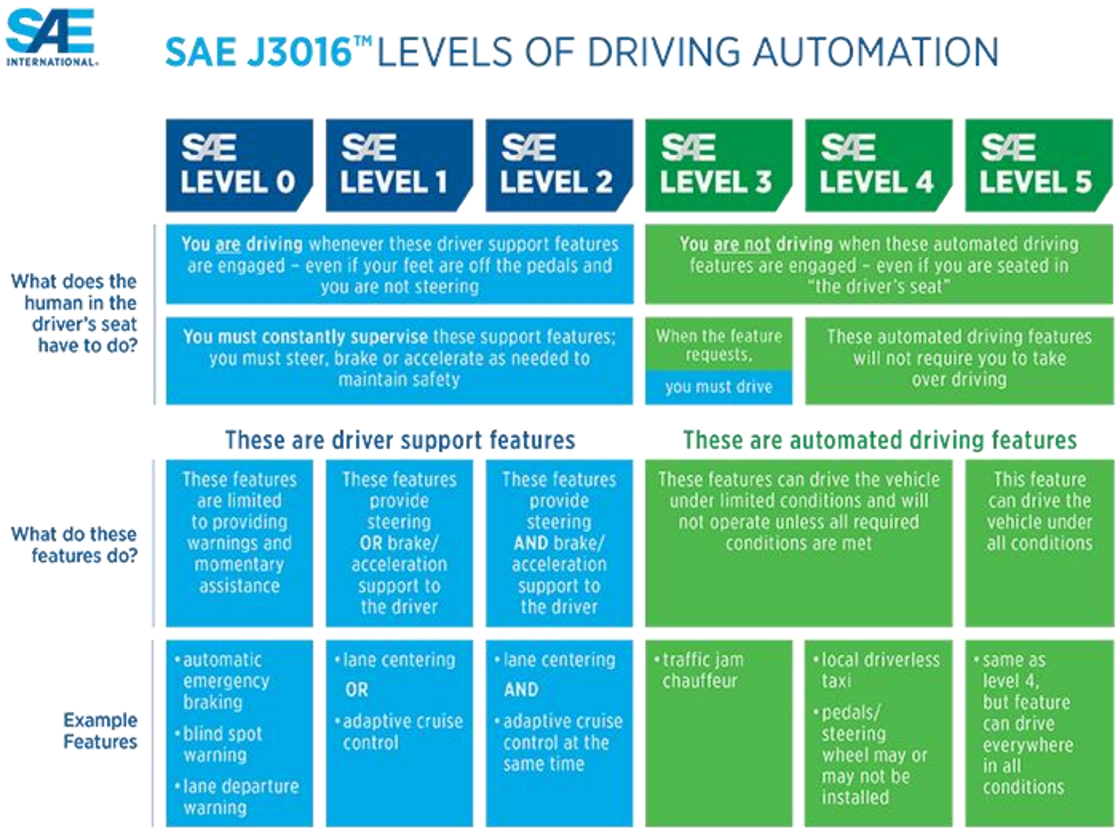
--- Table 7 here ---

--- Figure 10 here ---

Table 8 shows the trends of proportion of occupied subclasses of 1,197 patents based on EPO's classification. Except for 2001 and 2008, subclasses fall into the subcategory 'Perception, analysis & decision' with the highest rate. Next highest occupancy rate is shown in subcategory 'Smart Logistics', followed by 'Communication'. Next was 'Vehicle handling', and the lowest occupancy rate is shown in subcategory 'Computing'.

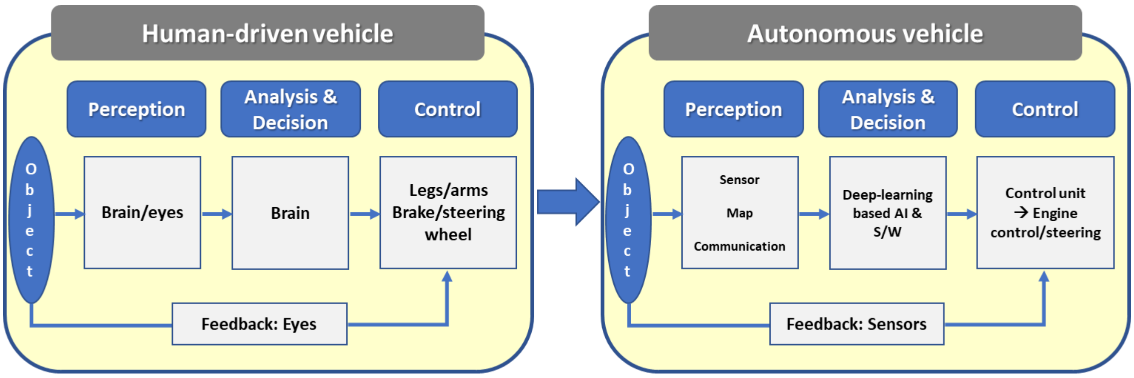
--- Table 8 here ---

Figure 1. Levels of driving automation



Source: SAE International

Figure 2. Operational process of human-driven vehicle and autonomous vehicle



Source: KDB Future Strategy Research Institute

Figure 3. Industries of top 20 Companies - Frequency

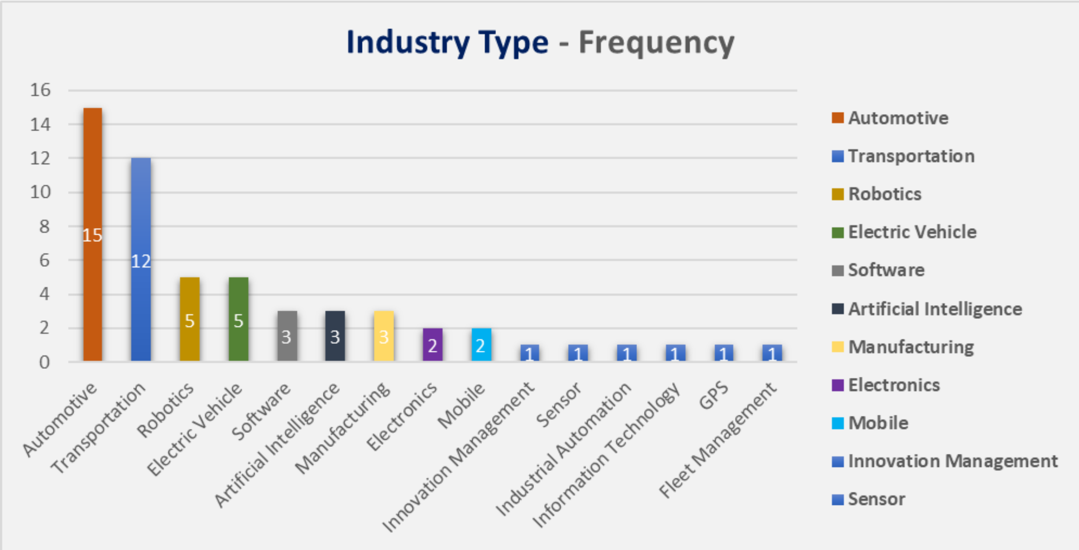


Figure 4. Number of companies by country

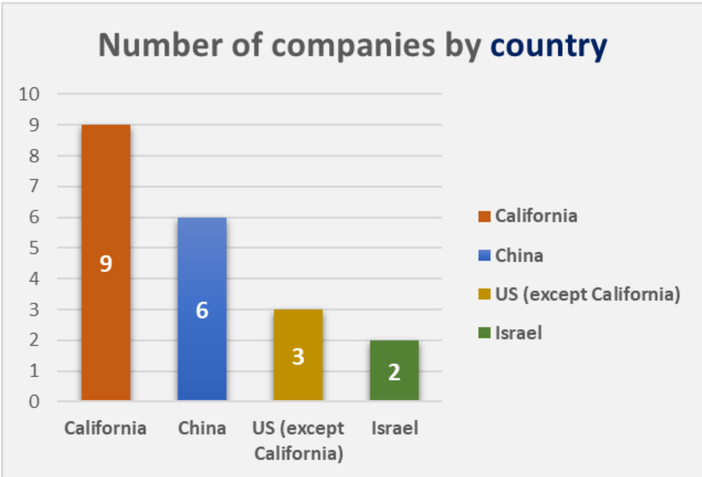
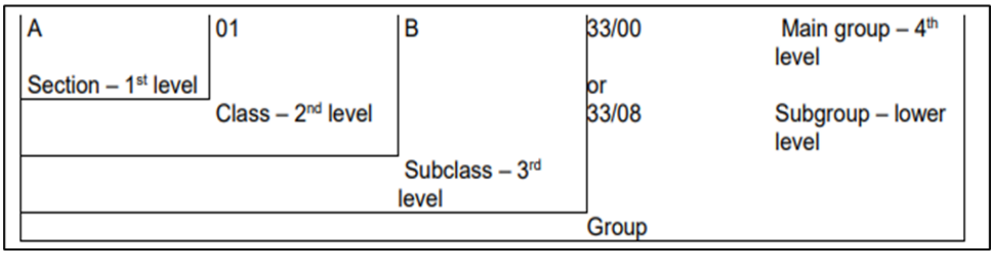


Figure 5. CPC Code hierarchy – example code A01B 33/08



Source: World Intellectual Property Organization

Figure 6. Number of patents filed by the 20 companies (2000-2019)

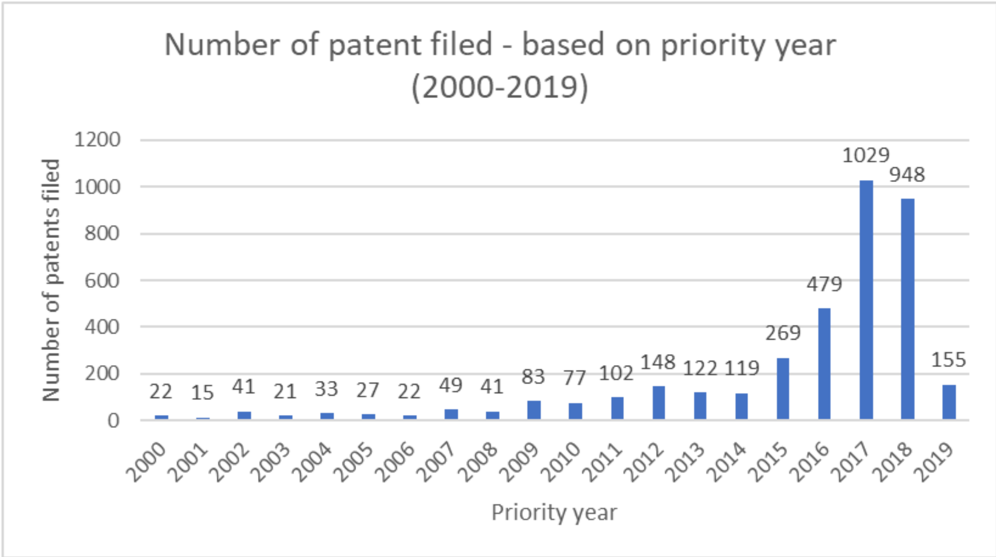


Figure 7. Frequency of 10 most occupied subclasses overtime (2000-2019)

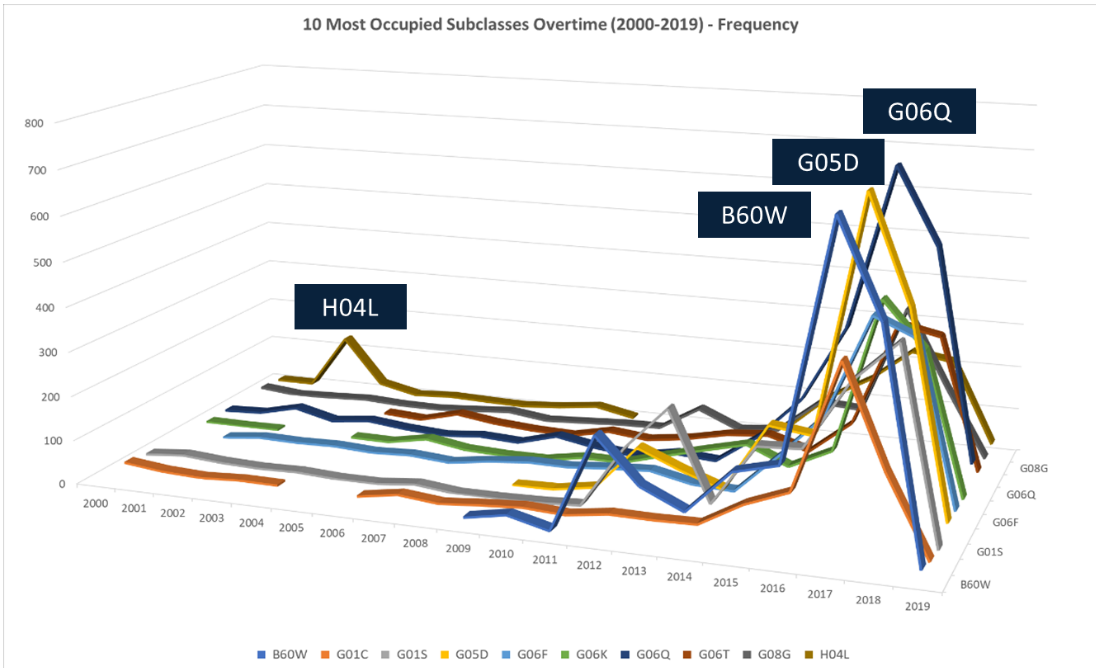


Figure 8. Frequency of 10 most occupied technological positions overtime (2000-2019)

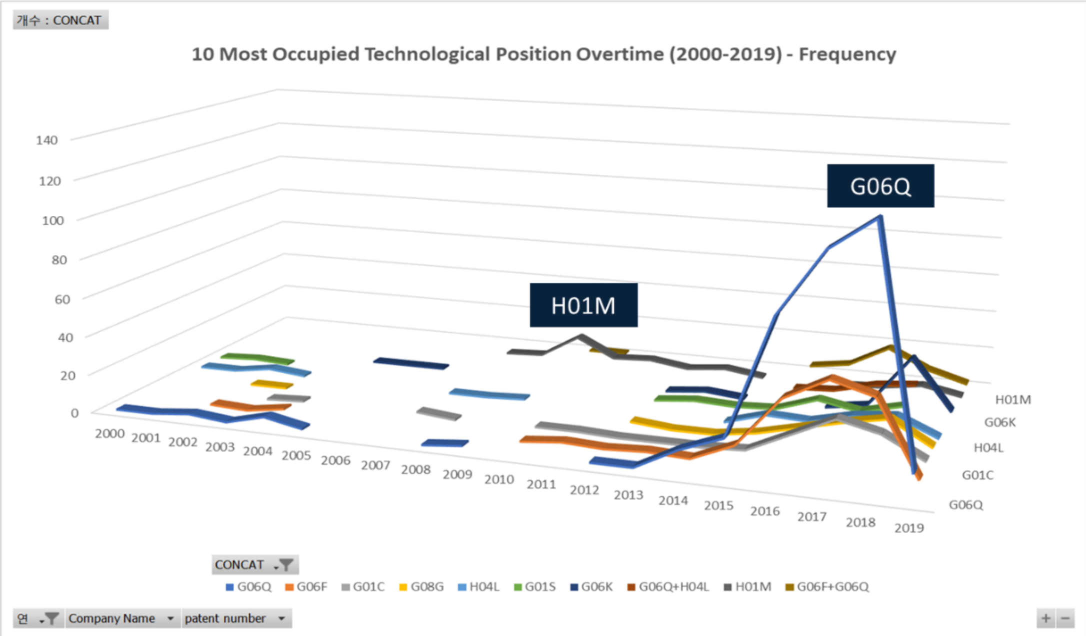


Figure 9. Interfirm overlap of technological positions of 20 firms

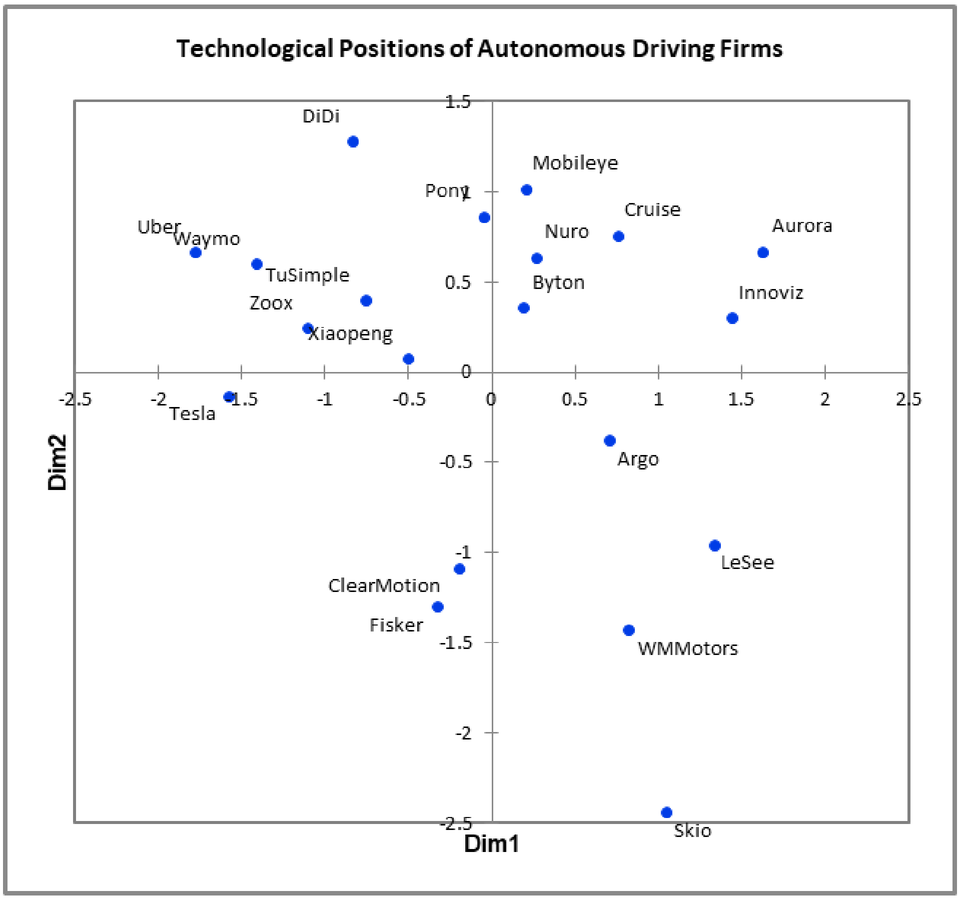


Figure 10. Frequency of technological positions of the patents based on EPO's classification (2000 to 2019)

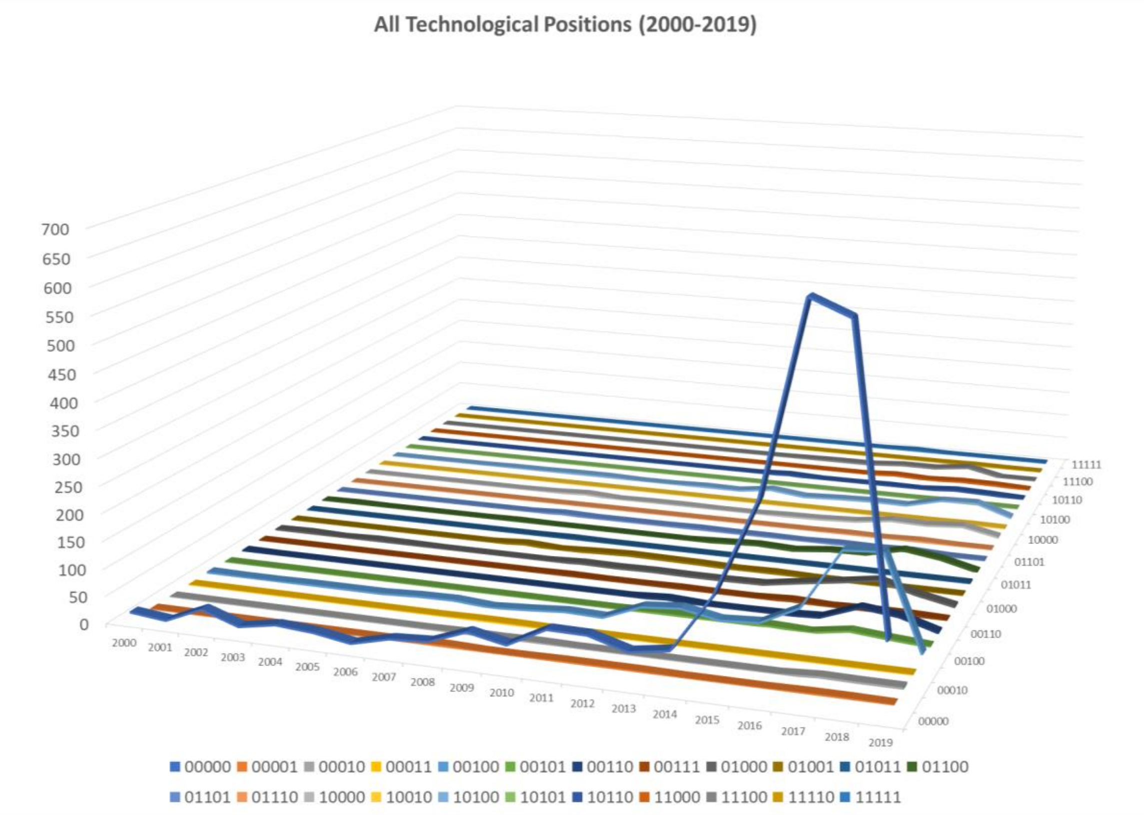


Table 1. Search filter on Crunchbase Pro's query builder

Filter Title	Contents
Industries	Autonomous Vehicles
Founded Date	After 01/01/2000
Total Equity Funding Amount	Greater than or equal to $10,000,000
Company Type	For Profit
Operating Status	Active

Table 2. Top 20 firms according to the total equity funding amount

Organization Name	Industry Category	Headquarters Location	Total Equity Funding Amount (in Million USD)	Founding Year
Cruise	Automotive, Autonomous Vehicles, Robotics, Software, Transportation	San Francisco, California, United States	5,267	2013
Tesla	Automotive, Autonomous Vehicles, Electric Vehicle, Electronics, Innovation Management	Palo Alto, California, United States	5,257	2003
Argo AI	Artificial Intelligence, Autonomous Vehicles, Transportation	Pittsburgh, Pennsylvania, United States	3,600	2016
Waymo	Automotive, Autonomous Vehicles, Robotics, Sensor, Transportation	Mountain View, California, United States	3,000	2009
Xiaopeng Motors	Automotive, Autonomous Vehicles, Electric Vehicle, Manufacturing	Guangzhou, Guangdong, China	2,191	2014
WM Motor	Automotive, Autonomous Vehicles, Mobile	Shanghai, Shanghai, China	1,597	2015

BYTON	Automotive, Autonomous Vehicles, Electric Vehicle	Nanjing, Jiangsu, China	1,200	2016
LeSee	Automotive, Autonomous Vehicles, Industrial Automation	Beijing, Beijing, China	1,080	2015
Nuro	Artificial Intelligence, Autonomous Vehicles, Electronics, Information Technology, Robotics	Mountain View, California, United States	1,032	2016
Uber Advanced Technologies Group	Automotive, Autonomous Vehicles, Transportation	Pittsburgh, Pennsylvania, United States	1,000	2015
Fisker Automotive	Automotive, Autonomous Vehicles, Electric Vehicle, Manufacturing, Mobile, Transportation	Anaheim, California, United States	998	2007
Zoox	Autonomous Vehicles, Robotics, Transportation	Foster City, California, United States	755	2014
Pony.ai	Artificial Intelligence, Automotive, Autonomous Vehicles, Information Technology, Software, Transportation	Fremont, California, United States	726	2016
Aurora Innovation	Automotive, Autonomous Vehicles, Machine Learning, Transportation	Palo Alto, California, United States	690	2017
Mobileye, an Intel Company	Artificial Intelligence, Automotive, Autonomous	Jerusalem, Yerushalayim, Israel	515	1999

	Vehicles, Fleet Management, Machine Learning, Transportation			
DiDi Autonomous Driving	Automotive, Autonomous Vehicles	Beijing, Beijing, China	500	2016
SKIO Matrix	Automotive, Autonomous Vehicles, Electric Vehicle, Transportation	Hangzhou, Zhejiang, China	299	2009
TuSimple	Artificial Intelligence, Autonomous Vehicles, Transportation	San Diego, California, United States	298	2015
ClearMotion	Automotive, Autonomous Vehicles, Manufacturing, Software, Transportation	Billerica, Massachusetts, United States	279	2009
Innoviz Technologies	Artificial Intelligence, Automotive, Autonomous Vehicles, GPS, Robotics	Tel Aviv, Tel Aviv, Israel	252	2016

Table 3. Description of 10 most occupied subclasses overtime

Rank	Subclass Symbol	Description	Frequency
1	B60W	Conjoint control of vehicle sub-units of different type or different function; Control systems specially adapted for hybrid vehicles; Road vehicle drive control systems for purposes not related to the control of a particular sub-unit	2,194
2	G06Q	Data processing systems or methods, specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes; Systems of methods specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes, not otherwise provided for	2,076
3	G05D	Systems for controlling or regulating non-electric variables (for continuous casting of metals B22D 11/16; valves per se F16K; sensing non-electric variables, see the relevant subclasses of G01; for regulating electric or magnetic variables G05F)	1,863
4	G01S	Radio direction-finding; Radio navigation; Determining distance of velocity by use of radio waves; Locating or presence-detecting by use of the reflection or reradiation of radio waves; Analogous arrangements using other waves	1,638
5	G06F	Electric digital data processing (computer systems based on specific computational models G06N)	1,354
6	G06K	Recognition of data; Presentation of data; Record carriers; Handling record carriers	1,209
7	G06T	Image data processing or generation, in general	1,041
8	G01C	Measuring distances, levels or bearing; Surveying; Navigation; Gyroscopic instruments; Photogrammetry or videogrammetry (measuring liquid level G01F; radio navigation, determining distance or velocity by use of propagation effects, e.g. Doppler effects, propagation time, of radio waves, analogous arrangements using other waves G01S)	1,031
9	G08G	Traffic control systems (guiding railway traffic, ensuring the safety of railway traffic B61L; arrangement of road signs or traffic signals E01F 9/00; radar or analogous systems, sonar systems, lidar systems specially adapted for traffic control G01S 13/91, G01S 15/88, G01S 17/88; {radar or analogous systems, sonar systems, lidar systems specially adapted for anti-collision purposes G01S 13/93, G01S 15/93, G01S 17/93})	1,008

10	H04L	Transmission of digital information, e.g. telegraphic communication (typewriters B41J; order telegraphs, fire or police telegraphs G08B; visual telegraphy G08B, G08C; teleautographic systems G08C; ciphering or deciphering apparatus per se G09C; coding, decoding or code conversion, in general H03M; arrangements common to telegraphic and telephonic communication H04M; selecting H04Q)	977

Table 4. 10 most occupied technological position of patents

Rank	Subclass Combination	Description	Frequency
1	G06Q	Data processing systems or methods, specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes; Systems or methods specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes, not otherwise provided for	387
2	G06F	Electric digital data processing (computer systems based on specific computational models G06N)	161
3	G01C	Measuring distances, levels or bearing; Surveying; Navigation; Gyroscopic instruments; Photogrammetry or videogrammetry (measuring liquid level G01F; radio navigation, determining distance or velocity by use of propagation effects, e.g. Doppler effects, propagation time, of radio waves, analogous arrangements using other waves G01S)	78
4	G08G	Traffic control systems (guiding railway traffic, ensuring the safety of railway traffic B61L; arrangement of road signs or traffic signals E01F 9/00; radar or analogous systems, sonar systems, lidar systems specially adapted for traffic control G01S 13/91, G01S 15/88, G01S 17/88; {radar or analogous systems, sonar systems, lidar systems specially adapted for anti-collision purposes G01S 13/93, G01S 15/93, G01S 17/93})	61
5	H04L	Transmission of digital information, e.g. telegraphic communication (typewriters B41J; order telegraphs, fire or police telegraphs G08B; visual telegraphy G08B, G08C; teleautographic systems G08C; ciphering or deciphering apparatus per se G09C; coding, decoding or code conversion, in general H03M; arrangements common to telegraphic and telephonic communication H04M; selecting H04Q)	55
6	G01S	Radio direction-finding; Radio navigation; Determining distance of velocity by use of radio waves; Locating or presence-detecting by use of the reflection or reradiation of radio waves; Analogous arrangements using other waves	51
7	G06K	Recognition of data; Presentation of data; Record carriers; Handling record carriers	50
8	G06Q+H04L	Data processing systems or methods, specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes; Systems or methods specially adapted for	47

		administrative, commercial, financial, managerial, supervisory or forecasting purposes, not otherwise provided for + Transmission of digital information, e.g. telegraphic communication (typewriters B41J; order telegraphs, fire or police telegraphs G08B; visual telegraphy G08B, G08C; teleautographic systems G08C; ciphering or deciphering apparatus per se G09C; coding, decoding or code conversion, in general H03M; arrangements common to telegraphic and telephonic communication H04M; selecting H04Q)	
9	H01M	Processes or means, e.g. batteries, for the direct conversion of chemical energy into electrical energy	42
10	G06F+G06Q	Electric digital data processing (computer systems based on specific computational models G06N) + Data processing systems or methods, specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes; Systems or methods specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes, not otherwise provided for	41

Table 5. Community matrix of 20 firms

Firm	Cruise	Tesla	Argo	Waymo	Xiaopeng	WM Moto	Byton	LeSee	Nuro	Uber	Fisker	Zoox	Pony	Aurora	Mobileye	DiDi	Skio	TuSimple	ClearMoti	Innoviz
Cruise	0	0.761905	0.285714	0.857143	0.761905	0.142857	0.761905	0.095238	0.714286	0.904762	0.190476	0.952381	0.714286	0.428571	0.761905	0.904762	0	0.761905	0.238095	0.333333
Tesla	0.164948	0	0.164948	0.43299	0.226804	0.061856	0.226804	0.051546	0.206186	0.515464	0.206186	0.391753	0.247423	0.082474	0.237113	0.402062	0.010309	0.257732	0.185567	0.061856
Argo	0.24	0.64	0	0.64	0.4	0	0.28	0	0.48	0.68	0.16	0.36	0.44	0.28	0.44	0.68	0	0.44	0.24	0.16
Waymo	0.26087	0.608696	0.231884	0	0.333333	0.086957	0.347826	0.072464	0.318841	0.826087	0.202899	0.521739	0.463768	0.15942	0.391304	0.681159	0.014493	0.521739	0.304348	0.130435
Xiaopeng	0.5	0.6875	0.3125	0.71875	0	0.1875	0.5625	0.09375	0.53125	0.84375	0.21875	0.78125	0.59375	0.3125	0.5625	0.78125	0.03125	0.5625	0.21875	0.25
WM Motors	0.428571	0.857143	0	0.857143	0.857143	0	0.857143	0.428571	0.285714	0.857143	0.714286	1	0.428571	0	0.714286	0.571429	0.142857	0.571429	0.285714	0.142857
Byton	0.551724	0.758621	0.241379	0.827586	0.62069	0.206897	0	0.103448	0.448276	0.896552	0.413793	0.793103	0.517241	0.275862	0.586207	0.827586	0	0.586207	0.241379	0.241379
LeSee	0.333333	0.833333	0	0.833333	0.5	0.5	0.5	0	0.166667	0.833333	0.333333	0.833333	0.5	0	0.5	0.5	0	0.5	0.166667	0.166667
Nuro	0.416667	0.555556	0.333333	0.611111	0.472222	0.055556	0.361111	0.027778	0	0.75	0.111111	0.5	0.5	0.305556	0.527778	0.722222	0	0.555556	0.222222	0.194444
Uber	0.180952	0.47619	0.161905	0.542857	0.257143	0.057143	0.247619	0.047619	0.257143	0	0.152381	0.390476	0.314286	0.104762	0.247619	0.561905	0.009524	0.390476	0.190476	0.095238
Fisker	0.148148	0.740741	0.148148	0.518519	0.259259	0.185185	0.444444	0.074074	0.148148	0.592593	0	0.444444	0.222222	0.074074	0.333333	0.444444	0.037037	0.259259	0.296296	0.074074
Zoox	0.4	0.76	0.18	0.72	0.5	0.14	0.46	0.1	0.36	0.82	0.24	0	0.46	0.2	0.48	0.58	0.02	0.5	0.26	0.18
Pony	0.384615	0.615385	0.282051	0.820513	0.487179	0.076923	0.384615	0.076923	0.461538	0.846154	0.153846	0.589744	0	0.282051	0.564103	0.692308	0	0.717949	0.282051	0.230769
Aurora	0.818182	0.727273	0.636364	1	0.909091	0	0.727273	0	1	1	0.181818	0.909091	1	0	1	1	0	1	0.363636	0.454545
Mobileye	0.533333	0.766667	0.366667	0.9	0.6	0.166667	0.566667	0.1	0.633333	0.866667	0.3	0.8	0.733333	0.366667	0	0.8	0	0.8	0.266667	0.3
DiDi	0.22093	0.453488	0.197674	0.546512	0.290698	0.046512	0.27907	0.034884	0.302326	0.686047	0.139535	0.337209	0.313953	0.127907	0.27907	0	0	0.348837	0.186047	0.116279
Skio	0	1	0	1	1	1	0	0	0	1	1	1	0	0	0	0	0	1	1	0
TuSimple	0.340426	0.531915	0.234043	0.765957	0.382979	0.085106	0.361702	0.06383	0.425532	0.87234	0.148936	0.531915	0.595745	0.234043	0.510638	0.638298	0.021277	0	0.234043	0.191489
ClearMotion	0.15625	0.5625	0.1875	0.65625	0.21875	0.0625	0.21875	0.03125	0.25	0.625	0.25	0.40625	0.34375	0.125	0.25	0.5	0.03125	0.34375	0	0.0625
Innoviz	0.7	0.6	0.4	0.9	0.8	0.1	0.7	0.1	0.7	1	0.2	0.9	0.9	0.5	0.9	1	0	0.9	0.2	0

Table 6. Distance matrix of 20 firms

	Cruise	Tesla	Argo	Waymo	Xiaopeng	WMMotor	Byton	LeSee	Nuro	Uber	Fisker	Zoox	Pony	Aurora	Mobileye	DiDi	Skio	TuSimple	ClearMoti	Innoviz
Cruise	0.0000	2.3363	1.9541	2.0716	1.2615	2.0191	0.8098	1.8521	1.0049	2.4602	2.0927	1.7264	0.9732	1.0544	0.7181	1.8586	2.9214	1.5504	1.9648	0.8789
Tesla	2.3363	0.0000	2.2560	0.8829	1.4716	2.6994	1.8242	2.7802	1.8726	0.8463	1.8010	1.0171	1.7473	3.1528	1.9580	1.3173	3.5237	1.2286	1.8261	2.9488
Argo	1.9541	2.2560	0.0000	2.3867	1.8330	1.9735	1.5046	1.4234	0.9601	2.6272	1.5661	2.2161	1.3850	1.6772	1.6662	1.9025	2.5335	1.8059	1.2388	1.4173
Waymo	2.0716	0.8829	2.3867	0.0000	1.2022	2.8432	1.6801	2.9901	1.7624	0.5204	2.2528	0.7106	1.4475	2.8777	1.5886	1.2211	3.7235	0.8565	2.1719	2.7568
Xiaopeng	1.2615	1.4716	1.8330	1.2022	0.0000	1.9800	1.0969	2.2675	1.3219	1.6080	1.7004	0.7740	1.2158	1.9947	1.1063	1.6321	3.1030	0.7057	1.6646	1.8322
WMMotor	2.0191	2.6994	1.9735	2.8432	1.9800	0.0000	1.9749	1.2618	2.3616	3.2187	1.3686	2.3672	2.4500	2.0762	2.3776	3.0898	1.8761	2.3863	1.6425	1.7914
Byton	0.8098	1.8242	1.5046	1.6801	1.0969	1.9749	0.0000	1.8300	1.0267	2.0228	1.8888	1.3233	0.8651	1.7389	0.6598	1.4726	2.8517	1.3776	1.8700	1.4780
LeSee	1.8521	2.7802	1.4234	2.9901	2.2675	1.2618	1.8300	0.0000	1.9921	3.3095	1.4811	2.6259	2.1958	1.9723	2.2184	2.8279	1.8210	2.5141	1.5815	1.5812
Nuro	1.0049	1.8726	0.9601	1.7624	1.3219	2.3616	1.0267	1.9921	0.0000	2.0185	1.8861	1.6371	0.6157	1.5692	0.9629	1.2139	2.9981	1.2428	1.6733	1.5031
Uber	2.4602	0.8463	2.6272	0.5204	1.6080	3.2187	2.0228	3.3095	2.0185	0.0000	2.4856	1.0521	1.7432	3.3012	1.9672	1.1953	4.0143	1.1934	2.3903	3.1495
Fisker	2.0927	1.8010	1.5661	2.2528	1.7004	1.3686	1.8888	1.4811	1.8861	2.4856	0.0000	1.9676	2.0788	2.5572	2.2507	2.3693	2.1907	1.8449	0.7101	2.1981
Zoox	1.7264	1.0171	2.2161	0.7106	0.7740	2.3672	1.3233	2.6259	1.6371	1.0521	1.9676	0.0000	1.3640	2.6175	1.3715	1.3895	3.4188	0.8003	2.0062	2.4357
Pony	0.9732	1.7473	1.3850	1.4475	1.2158	2.4500	0.8651	2.1958	0.6157	1.7432	2.0788	1.3640	0.0000	1.7263	0.6076	1.0480	3.1056	1.0454	1.9238	1.5990
Aurora	1.0544	3.1528	1.6772	2.8777	1.9947	2.0762	1.7389	1.9723	1.5692	3.3012	2.5572	2.6175	1.7263	0.0000	1.5461	2.7068	3.0182	2.2252	2.3819	0.6162
Mobileye	0.7181	1.9580	1.6662	1.5886	1.1063	2.3776	0.6598	2.2184	0.9629	1.9672	2.2507	1.3715	0.6076	1.5461	0.0000	1.4089	3.1458	1.2414	2.1327	1.4628
DiDi	1.8586	1.3173	1.9025	1.2211	1.6321	3.0898	1.4726	2.8279	1.2139	1.1953	2.3693	1.3895	1.0480	2.7068	1.4089	0.0000	3.6513	1.3006	2.2180	2.5477
Skio	2.9214	3.5237	2.5335	3.7235	3.1030	1.8761	2.8517	1.8210	2.9981	4.0143	2.1907	3.4188	3.1056	3.0182	3.1458	3.6513	0.0000	3.2726	2.2106	2.7536
TuSimple	1.5504	1.2286	1.8059	0.8565	0.7057	2.3863	1.3776	2.5141	1.2428	1.1934	1.8449	0.8003	1.0454	2.2252	1.2414	1.3006	3.2726	0.0000	1.6727	2.0937
ClearMoti	1.9648	1.8261	1.2388	2.1719	1.6646	1.6425	1.8700	1.5815	1.6733	2.3903	0.7101	2.0062	1.9238	2.3819	2.1327	2.2180	2.2106	1.6727	0.0000	2.0411
Innoviz	0.8789	2.9488	1.4173	2.7568	1.8322	1.7914	1.4780	1.5812	1.5031	3.1495	2.1981	2.4357	1.5990	0.6162	1.4628	2.5477	2.7536	2.0937	2.0411	0.0000

Table 7. Technology vector of the patents based on EPO's classification

Row Labels	00000	00001	00010	00011	00100	00101	00110	00111	01000	01001	01011	01100	01101	01110	10000	10010	10100	10101	10110	11000	11100	11110	11111	Grand Total
2000	18				2		1		1															22
2001	11				1				2			1												15
2002	40				1																			41
2003	17				2				2															21
2004	29				2				1								1							33
2005	24				2												1							27
2006	13				5							1			1		2							22
2007	30				6					4			3		4		2							49
2008	34	2	1	1	1						1		1											41
2009	60			1	5			1	3	3			1		1									75
2010	46		1		10				2	5			1		1		2							68
2011	82	1			8				3	4			2				1							101
2012	81	1			36	2	4	1	2	3		3	1				10		3		1			148
2013	61	1			42	2			2	1		6	1		2		2				2			122
2014	72				29				3	2		3			3		5				2			119
2015	174				33	3	1	3	14			10	2	1	6		7		1	4	7		2	268
2016	340				68		4		24			11	1		15		6			1	7			477
2017	670	1	4		179	11	30	2	35			27	3	2	13		23	1	5	4	15	1		1026
2018	642	1	3		184	5	22	2	16			17			18	1	25		3	3				942
2019	132		3		11		1		2						4		2							155
2020					1																			1
Grand Total	2576	7	12	2	628	23	63	9	112	22	1	79	16	3	68	1	89	1	12	12	34	1	2	3773

Table 8. Proportion of occupied subclasses based on EPO's classification

	Communication	Smart Logistics	Perception, analysis & decision	Computing	Vehicle handling
2000	0%	20%	50%	30%	0%
2001	0%	60%	40%	0%	0%
2002	0%	0%	100%	0%	0%
2003	0%	50%	50%	0%	0%
2004	22%	11%	67%	0%	0%
2005	20%	0%	80%	0%	0%
2006	17%	6%	78%	0%	0%
2007	14%	35%	35%	0%	16%
2008	0%	21%	14%	21%	43%
2009	9%	39%	27%	6%	18%
2010	6%	31%	44%	2%	17%
2011	2%	34%	48%	0%	16%
2012	9%	10%	74%	4%	4%
2013	5%	12%	79%	0%	4%
2014	8%	11%	80%	0%	1%
2015	12%	17%	64%	2%	5%
2016	10%	16%	72%	2%	0%
2017	10%	13%	70%	5%	2%
2018	10%	7%	76%	5%	2%
2019	18%	6%	64%	12%	0%